

## 1. Introduction

\*No Deliverables\*

## 2. Multivariate Gaussian Distributions and Whitening

1. Scatter plots for  $W$ ,  $\tilde{X}$ , and  $X$

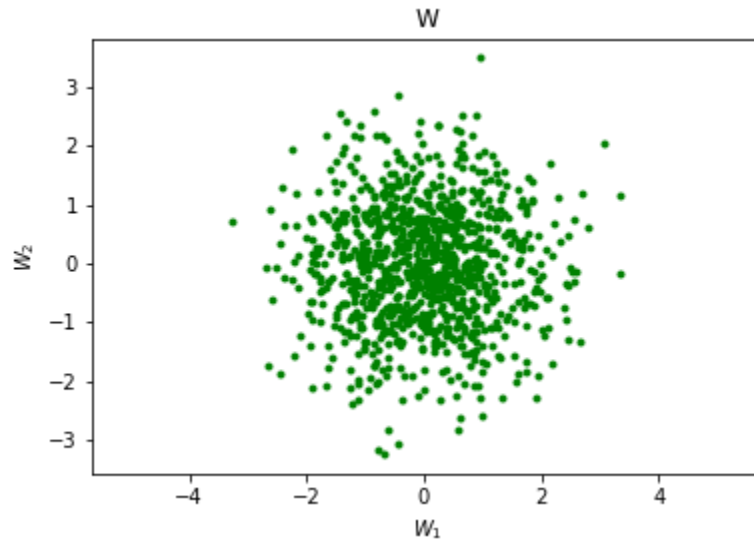


Figure 1:  $W$

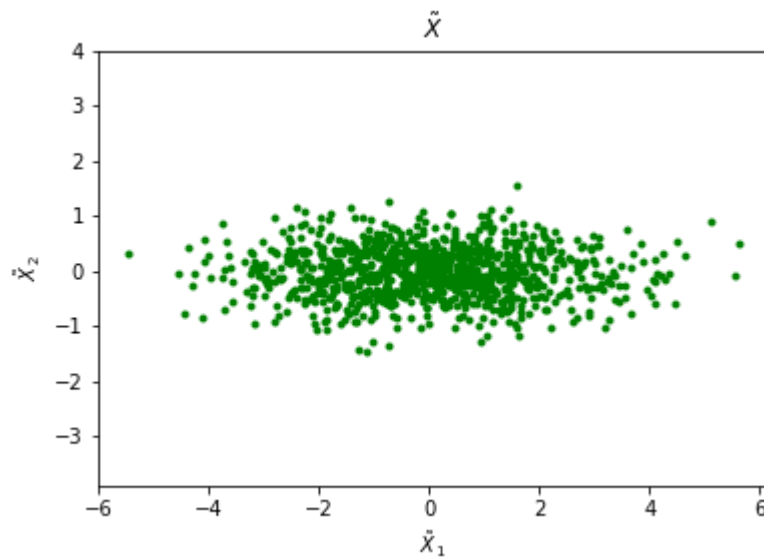


Figure 2:  $\tilde{X}$

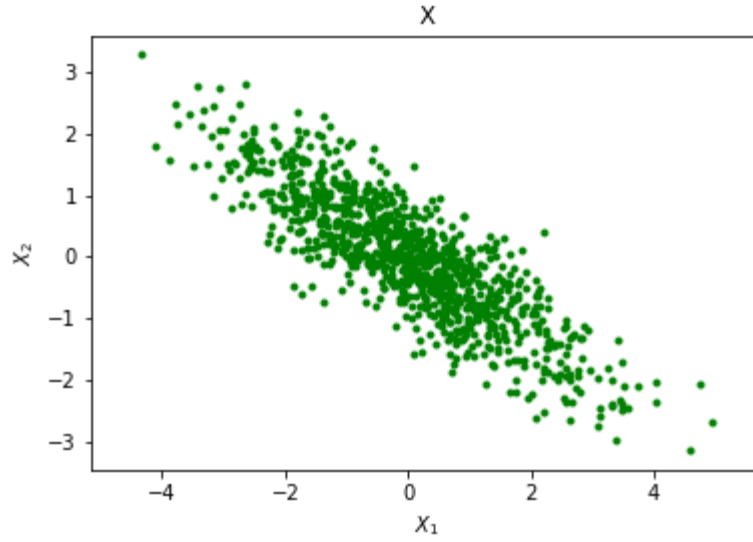


Figure 3:  $X$

2. Print out of the image showing the connected set for  $s = (67, 45)$ , and  $T = 3$ 
  - a. Theoretical value of the covariance matrix  $R_X$

$$R_X = \begin{bmatrix} 2 & -1.2 \\ -1.2 & 1 \end{bmatrix}$$

- b. Numerical listing of covariance estimate  $\hat{R}_X$

$$\hat{R}_X = \begin{bmatrix} 2.002 & -1.211 \\ -1.211 & 1.021 \end{bmatrix}$$

- c. Scatter plots for  $\tilde{X}$  and  $W$

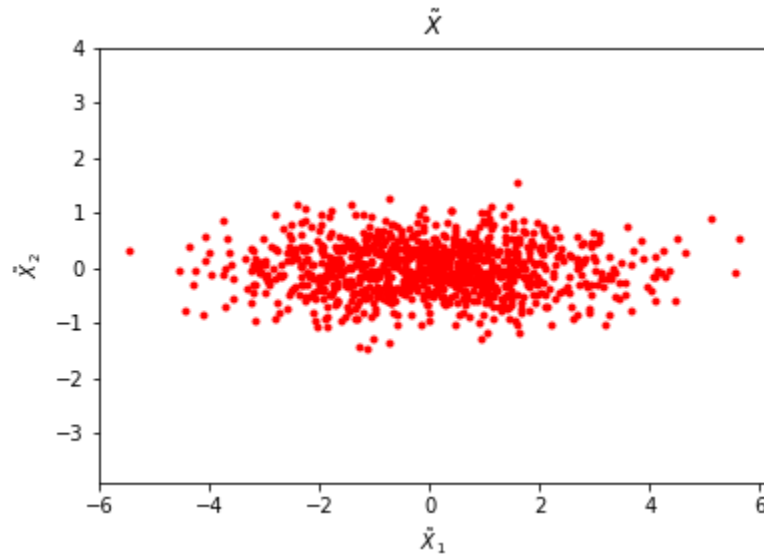
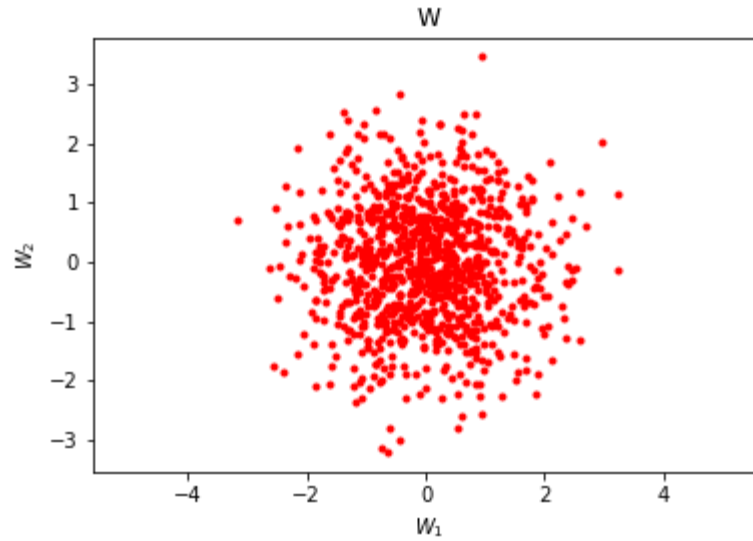


Figure 4:  $\tilde{X}$



*Figure 5: W*

d. Numerical listing of covariance estimate  $\hat{R}_W$

$$\hat{R}_W = \begin{bmatrix} 1.006 & -0.018 \\ -0.018 & 1.026 \end{bmatrix}$$

### 3. Estimation of Eigenvectors and Eigenvalues Using the Singular Value Decomposition

\*No Deliverables\*

## 4. Eigenimages, PCA, and Data Reduction

### 1. Figure of first 12 eigenimages

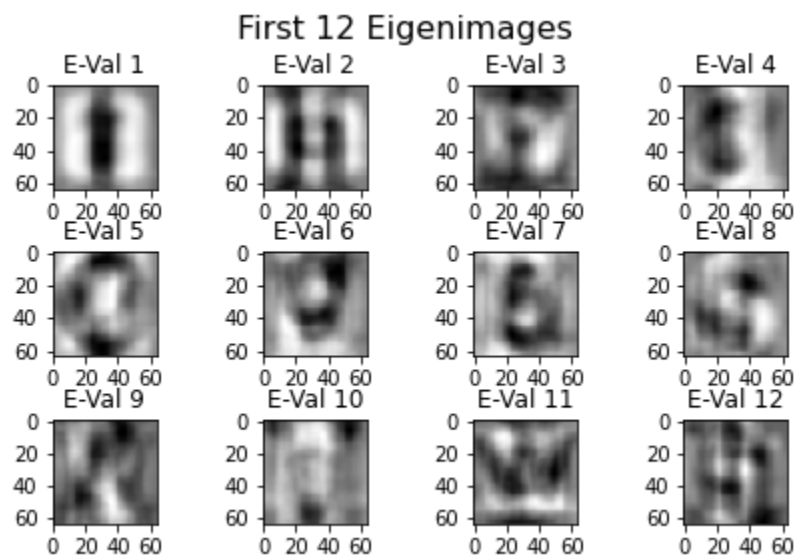


Figure 6: First 12 Eigenimages

### 2. Plot of projection coefficients vs. eigenvector number

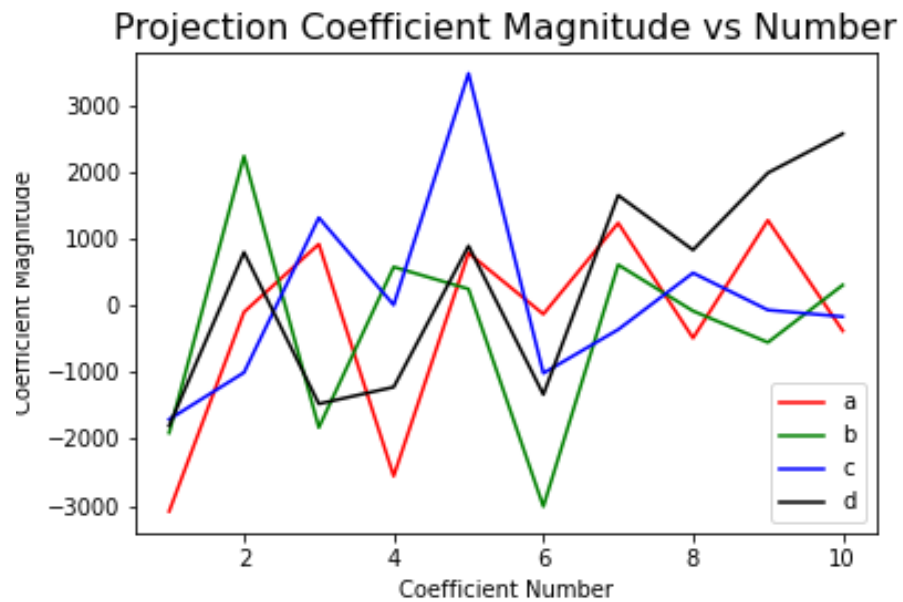


Figure 7: Projection Coefficients vs Eigenvector Number

### 3. Original image and the 6 resynthesized versions

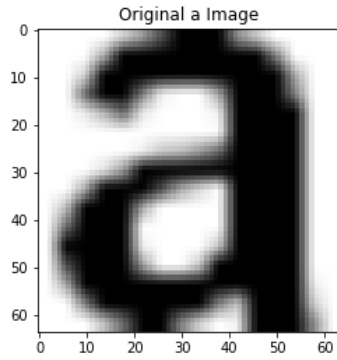


Figure 8: Original 'a' Image

### 6 Resynthesized Versions

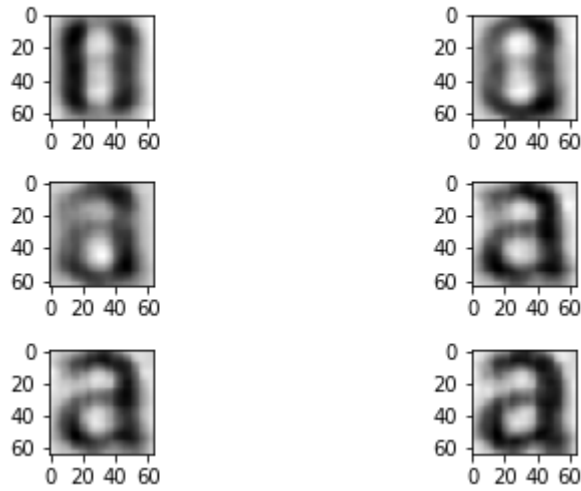


Figure 9: 6 Resynthesized versions of 'a'

## 5. Image Classification

### 1. Mis-classified image list using $R_k$

| Actual Letter | Mis-Classified As |
|---------------|-------------------|
| d             | a                 |
| j             | y                 |
| l             | i                 |
| n             | v                 |
| p             | e                 |
| q             | a                 |
| u             | a                 |
| y             | v                 |

2. Mis-classified image lists using various  $B_k$

a. Using  $B_k = \Lambda_k$

| Actual Letter | Mis-Classified As |
|---------------|-------------------|
| i             | l                 |
| y             | v                 |

b. Using  $B_k = R_{wc}$

| Actual Letter | Mis-Classified As |
|---------------|-------------------|
| g             | q                 |
| y             | v                 |

c. Using  $B_k = \Lambda$

| Actual Letter | Mis-Classified As |
|---------------|-------------------|
| f             | t                 |
| y             | v                 |

d. Using  $B_k = I$

| Actual Letter | Mis-Classified As |
|---------------|-------------------|
| f             | t                 |
| g             | q                 |
| y             | v                 |

3. Further Questions:

a. **1. Which of the above classifiers worked the best in this experiment?**

Classification using  $B_k = \Lambda_k$ ,  $B_k = R_{wc}$ , and  $B_k = \Lambda$  worked the best in this experiment. This is because these selections led to the least number of mis-classified letters

b. **In constraining the covariance, what is the trade off between the accuracy of the data model and the accuracy of the estimates?**

When the covariance is constrained, the accuracy of the estimates is increased as seen in the previous results. However, the accuracy of the data model is decreased because the ground-truth of the training data is not captured. When the covariance matrix is modified, certain statistical relationships among the training data are not maintained.